

# Gaussian Fading Is the Worst Fading

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## Abstract

The capacity of peak-power limited, single-antenna, noncoherent, flat-fading channels with memory is considered. The emphasis is on the capacity pre-log, i.e., on the limiting ratio of channel capacity to the logarithm of the signal-to-noise ratio (SNR), as the SNR tends to infinity. It is shown that, among all stationary & ergodic fading processes of a given spectral distribution function and whose law has no mass point at zero, the Gaussian process gives rise to the smallest pre-log. The assumption that the law of the fading process has no mass point at zero is essential in the sense that there exist stationary & ergodic fading processes whose law has a mass point at zero and that give rise to a smaller pre-log than the Gaussian process of equal spectral distribution function. An extension of our results to multiple-input single-output fading channels with memory is also presented.

## 1 Introduction

We study the capacity of peak-power limited, single-antenna, discrete-time, flat-fading channels with memory. A noncoherent channel model is considered where the transmitter and receiver are both aware of the law of the fading process, but not of its realization. Our focus is on the capacity at high signal-to-noise ratio (SNR). Specifically, we study the capacity pre-log, which is defined as the limiting ratio of channel capacity to the logarithm of the SNR, as the SNR tends to infinity.

The capacity pre-log of *Gaussian* fading channels was derived in [1] (see also [2]). It was shown that the pre-log is given by the Lebesgue measure of the set of harmonics where the derivative of the spectral distribution function that characterizes the memory of the fading process is zero. To the best of our knowledge, the capacity pre-log of *non-Gaussian* fading channels is unknown.

In this work, we demonstrate that the Gaussian assumption in the analysis of fading channels at high SNR is conservative in the sense that for a large class of fading processes the Gaussian process is the worst. More precisely, we show that among all stationary & ergodic fading processes of a given spectral distribution function and whose law has no mass point at zero, the Gaussian process gives rise to the smallest pre-log.

This paper is organized as follows. Section 2 describes the channel model. Section 3 defines channel capacity and the capacity pre-log. Section 4 presents our main results. Section 5 provides the proofs of these results. Section 6 discusses the extension of our results to multiple-input single-output (MISO) fading channels with memory. Section 7 concludes the paper with a summary and a discussion of our results.

## 2 Channel Model

Let  $\mathbb{C}$  and  $\mathbb{Z}$  denote the set of complex numbers and the set of integers. We consider a single-antenna flat-fading channel with memory where the time- $k$  channel output  $Y_k \in \mathbb{C}$  corresponding

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to the time- $k$  channel input  $x_k \in \mathbb{C}$  is given by

$$Y_k = H_k x_k + Z_k, \quad k \in \mathbb{Z}. \quad (1)$$

Here the random processes  $\{Z_k, k \in \mathbb{Z}\}$  and  $\{H_k, k \in \mathbb{Z}\}$  take value in  $\mathbb{C}$  and model the additive and multiplicative noises, respectively. It is assumed that these processes are statistically independent and of a joint law that does not depend on the input sequence  $\{x_k\}$ .

The additive noise  $\{Z_k, k \in \mathbb{Z}\}$  is a sequence of independent and identically distributed (IID) zero-mean, variance- $\sigma^2$ , circularly-symmetric, complex Gaussian random variables. The multiplicative noise (“fading”)  $\{H_k, k \in \mathbb{Z}\}$  is a mean- $d$ , unit-variance, stationary & ergodic stochastic process of spectral distribution function  $F(\lambda)$ ,  $-1/2 \leq \lambda \leq 1/2$ , i.e.,  $F(\cdot)$  is a bounded and nondecreasing function on  $[-1/2, 1/2]$  satisfying

$$\mathbb{E}[(H_{k+m} - d)(H_k - d)^*] = \int_{-1/2}^{1/2} e^{i2\pi m\lambda} dF(\lambda), \quad (k \in \mathbb{Z}, m \in \mathbb{Z}), \quad (2)$$

where  $i = \sqrt{-1}$ , and where  $A^*$  denotes the complex conjugate of  $A$  [3, p. 474, Thm. 3.2]. Since  $F(\cdot)$  is monotonic, it is almost everywhere differentiable, and we denote its derivative by  $F'(\cdot)$ . (At the discontinuity points of  $F(\cdot)$  the derivative  $F'(\cdot)$  is undefined.) For example, if the fading process  $\{H_k, k \in \mathbb{Z}\}$  is IID, then

$$F'(\lambda) = 1, \quad -\frac{1}{2} \leq \lambda \leq \frac{1}{2}.$$

### 3 Channel Capacity and the Pre-Log

Channel capacity is defined as the supremum of all achievable rates. (We refer to [4, Ch. 8] for a definition of an achievable rate and for a more detailed discussion of channel capacity.) It was shown (e.g., [5, Thm. 2]) that the capacity of our channel (1) under a peak-power constraint  $A^2$  on the inputs is given by

$$C(\text{SNR}) = \lim_{n \rightarrow \infty} \frac{1}{n} \sup I(X_1^n; Y_1^n); \quad (3)$$

where SNR is defined as

$$\text{SNR} \triangleq \frac{A^2}{\sigma^2}; \quad (4)$$

$A_m^n$  denotes the sequence  $A_m, \dots, A_n$ ; and where the maximization is over all joint distributions on  $X_1, \dots, X_n$  satisfying with probability one

$$|X_k|^2 \leq A^2, \quad k = 1, \dots, n. \quad (5)$$

The capacity pre-log is defined as [1]

$$\Pi \triangleq \overline{\lim}_{\text{SNR} \rightarrow \infty} \frac{C(\text{SNR})}{\log \text{SNR}}. \quad (6)$$

For *Gaussian fading*, i.e., when  $\{H_k - d, k \in \mathbb{Z}\}$  is a circularly-symmetric, complex Gaussian process, the pre-log  $\Pi_G$  is given by the Lebesgue measure of the set of harmonics where the derivative of the spectral distribution function is zero, i.e.,

$$\Pi_G = \mu(\{\lambda: F'(\lambda) = 0\}), \quad (7)$$

where  $\mu(\cdot)$  denotes the Lebesgue measure on the interval  $[-1/2, 1/2]$ ; see [1], [2]. (Here the subscript “G” stands for “Gaussian”.)

This result indicates that if the fading process is Gaussian and satisfies

$$\mu(\{\lambda: F'(\lambda) = 0\}) > 0,$$

then the corresponding channel capacity grows logarithmically in the SNR. Note that otherwise the capacity can increase with the SNR in various ways. For instance, in [6] fading channels are studied that result in a capacity which increases double-logarithmically with the SNR, and in [1] spectral distribution functions are presented for which capacity grows as a fractional power of the logarithm of the SNR.

## 4 Main Result

We show that, among all stationary & ergodic fading processes of a given spectral distribution function and whose law has no mass point at zero, the Gaussian process gives rise to the smallest pre-log. This is made precise in the following theorem.

**Theorem 1.** *Consider a mean-d, unit-variance, stationary & ergodic fading process  $\{H_k, k \in \mathbb{Z}\}$  whose spectral distribution function is given by  $F(\cdot)$  and whose law satisfies*

$$\Pr[H_k = 0] = 0, \quad k \in \mathbb{Z}.$$

*Then the corresponding capacity pre-log  $\Pi$  is lower bounded by*

$$\Pi \geq \mu(\{\lambda: F'(\lambda) = 0\}). \quad (8)$$

*Proof.* See Section 5.1. □

The assumption that the law of the fading process has no mass point at zero is essential in the following sense.

**Note 1.** *There exists a mean-d, unit-variance, stationary & ergodic fading process  $\{H_k, k \in \mathbb{Z}\}$  of some spectral distribution function  $F(\cdot)$  such that*

$$\Pi < \mu(\{\lambda: F'(\lambda) = 0\}). \quad (9)$$

*By Theorem 1, this process must satisfy*

$$\Pr[H_k = 0] > 0, \quad k \in \mathbb{Z}.$$

*Proof.* See Section 5.2. □

**Note 2.** *The inequality in (8) can be strict. For example, consider the phase-noise channel with memoryless phase noise. This channel can be viewed as a fading channel where the fading process  $\{H_k, k \in \mathbb{Z}\}$  is given by*

$$H_k = e^{i\Theta_k}, \quad k \in \mathbb{Z},$$

*and where  $\{\Theta_k, k \in \mathbb{Z}\}$  is IID with  $\Theta_k$  being uniformly distributed over  $[-\pi, \pi)$ . This process gives rise to a pre-log  $\Pi = 1/2$ , whereas the Gaussian fading of equal spectral distribution function yields  $\Pi_G = 0$ .*

*Proof.* For a derivation of the capacity pre-log of the phase-noise channel see Section 5.3. □

## 5 Proofs

This section provides the proofs of our main results. For a proof of Theorem 1 see Section 5.1, for a proof of Note 1 see Section 5.2, and for a proof of Note 2 see Section 5.3.

### 5.1 Proof of Theorem 1

To prove Theorem 1, we derive in Section 5.1.1 a lower bound on the capacity, and proceed in Section 5.1.2 to analyze its asymptotic growth as the SNR tends to infinity.

#### 5.1.1 Capacity Lower Bound

To derive a lower bound on the capacity we consider inputs  $\{X_k, k \in \mathbb{Z}\}$  that are IID, zero-mean, circularly-symmetric, and for which  $|X_k|^2$  is uniformly distributed over the interval  $[0, A^2]$ . Our derivation is based on the lower bound

$$\frac{1}{n}I(X_1^n; Y_1^n) \geq \frac{1}{n}I(X_1^n; Y_1^n | H_1^n) - \frac{1}{n}I(H_1^n; Y_1^n | X_1^n), \quad (10)$$

which follows from the chain rule

$$\begin{aligned} I(X_1^n; Y_1^n) &= I(X_1^n, H_1^n; Y_1^n) - I(H_1^n; Y_1^n | X_1^n) \\ &= I(H_1^n; Y_1^n) + I(X_1^n; Y_1^n | H_1^n) - I(H_1^n; Y_1^n | X_1^n) \end{aligned} \quad (11)$$

and the nonnegativity of mutual information.

We first study the first term on the right-hand side (RHS) of (10). Making use of the stationarity of the channel and of the fact that the inputs are IID we have

$$\frac{1}{n} I(X_1^n; Y_1^n | H_1^n) = I(X_1; Y_1 | H_1). \quad (12)$$

We lower bound the RHS of (12) as follows. For any fixed  $\Upsilon > 0$

$$\begin{aligned} I(X_1; Y_1 | H_1) &= h(H_1 X_1 + Z_1 | H_1) - h(Z_1) \\ &= \int_{|h_1| \geq \Upsilon} h(H_1 X_1 + Z_1 | H_1 = h_1) dP_{H_1}(h_1) \\ &\quad + \int_{|h_1| < \Upsilon} h(H_1 X_1 + Z_1 | H_1 = h_1) dP_{H_1}(h_1) - h(Z_1) \\ &\geq \int_{|h_1| \geq \Upsilon} h(H_1 X_1 + Z_1 | H_1 = h_1) dP_{H_1}(h_1) + \Pr[|H_1| < \Upsilon] h(Z_1) - h(Z_1) \\ &\geq \int_{|h_1| \geq \Upsilon} (\log |h_1|^2 + h(X_1)) dP_{H_1}(h_1) + \Pr[|H_1| < \Upsilon] h(Z_1) - h(Z_1) \\ &\geq \Pr[|H_1| \geq \Upsilon] (\log \Upsilon^2 + h(X_1)) + \Pr[|H_1| < \Upsilon] h(Z_1) - h(Z_1) \\ &= \Pr[|H_1| \geq \Upsilon] (\log \Upsilon^2 + \log \pi + h(|X_1|^2)) + \Pr[|H_1| < \Upsilon] h(Z_1) - h(Z_1) \\ &= \Pr[|H_1| \geq \Upsilon] \log A^2 + \Pr[|H_1| \geq \Upsilon] \log(\pi \Upsilon^2) + \Pr[|H_1| < \Upsilon] h(Z_1) - h(Z_1) \\ &= \Pr[|H_1| \geq \Upsilon] \log A^2 + \Pr[|H_1| \geq \Upsilon] \log(\pi \Upsilon^2) + (\Pr[|H_1| < \Upsilon] - 1) \log(\pi e \sigma^2) \\ &= \Pr[|H_1| \geq \Upsilon] \log \text{SNR} - \Pr[|H_1| \geq \Upsilon] (1 - \log \Upsilon^2), \end{aligned} \quad (13)$$

where  $P_{H_1}(\cdot)$  denotes the distribution function of the fading  $H_1$ . Here the third step follows by conditioning the entropy in the second integral on  $X_1$ ; the fourth step follows by conditioning the entropy in the first integral on  $Z_1$  and by the behavior of differential entropy under scaling [4, Thm. 9.6.4]; the fifth step follows because over the range of integration  $|h_1| \geq \Upsilon$  we have  $\log |h_1|^2 \geq \log \Upsilon^2$ ; the sixth step follows because  $X_1$  is circularly-symmetric [6, Lemma 6.16]; the seventh step follows by computing the entropy of a random variable that is uniformly distributed over the interval  $[0, A^2]$ ; the eighth step follows by evaluating the entropy of a zero-mean, variance- $\sigma^2$ , circularly-symmetric, complex Gaussian random variable  $h(Z_k) = \log(\pi e \sigma^2)$ ; and the last step follows from  $\Pr[|H_1| \geq \Upsilon] = 1 - \Pr[|H_1| < \Upsilon]$ .

We next turn to the second term on the RHS of (10). In order to upper bound it we proceed along the lines of [7], but for non-Gaussian fading. Let  $\mathbf{Y}$ ,  $\mathbf{H}$ , and  $\mathbf{Z}$  be the random vectors  $(Y_1, \dots, Y_n)^\top$ ,  $(H_1, \dots, H_n)^\top$ , and  $(Z_1, \dots, Z_n)^\top$  (where  $\mathbf{A}^\top$  denotes the transpose of  $\mathbf{A}$ ), and let  $\mathbf{X}$  be a diagonal matrix with diagonal entries  $x_1, \dots, x_n$ . It follows from (1) that

$$\mathbf{Y} = \mathbf{X}\mathbf{H} + \mathbf{Z}. \quad (14)$$

The conditional covariance matrix of  $\mathbf{Y}$ , conditional on  $x_1, \dots, x_n$ , is given by

$$\mathbb{E}[(\mathbf{Y} - \mathbb{E}[\mathbf{Y}])(\mathbf{Y} - \mathbb{E}[\mathbf{Y}])^\dagger \mid X_1^n = x_1^n] = \mathbf{X}\mathbf{K}_{\mathbf{H}\mathbf{H}}\mathbf{X}^\dagger + \sigma^2 \mathbf{I}_n, \quad (15)$$

where  $\mathbf{I}_n$  is the  $n \times n$  identity matrix,  $(\cdot)^\dagger$  denotes Hermitian conjugation, and

$$\mathbf{K}_{\mathbf{H}\mathbf{H}} \triangleq \mathbb{E}[(\mathbf{H} - \mathbb{E}[\mathbf{H}])(\mathbf{H} - \mathbb{E}[\mathbf{H}])^\dagger]. \quad (16)$$

Let  $\det \mathbf{A}$  denote the determinant of the matrix  $\mathbf{A}$ . Using the entropy maximizing property of

circularly-symmetric Gaussian vectors [4, Thm. 9.6.5], we have

$$\begin{aligned}
\frac{1}{n} I(H_1^n; Y_1^n | X_1^n) &= \frac{1}{n} h(Y_1^n | X_1^n) - \frac{1}{n} h(Z_1^n) \\
&\leq \frac{1}{n} \mathbb{E} \left[ \log \det \left( \mathbf{I}_n + \frac{1}{\sigma^2} \mathbb{X} \mathbf{K}_{\mathbf{H}\mathbf{H}} \mathbb{X}^\dagger \right) \right] \\
&= \frac{1}{n} \mathbb{E} \left[ \log \det \left( \mathbf{I}_n + \frac{1}{\sigma^2} \mathbf{K}_{\mathbf{H}\mathbf{H}} \mathbb{X}^\dagger \mathbb{X} \right) \right] \\
&\leq \frac{1}{n} \log \det \left( \mathbf{I}_n + \frac{\mathbf{A}^2}{\sigma^2} \mathbf{K}_{\mathbf{H}\mathbf{H}} \right) \\
&= \frac{1}{n} \log \det (\mathbf{I}_n + \text{SNR} \mathbf{K}_{\mathbf{H}\mathbf{H}}) \\
&= \frac{1}{n} \sum_{k=1}^n \log(1 + \text{SNR} \lambda_k), \tag{17}
\end{aligned}$$

where  $\mathbb{X}$  is a random diagonal matrix with diagonal entries  $X_1, \dots, X_n$ , and where  $\lambda_1, \dots, \lambda_n$  denote the eigenvalues of  $\mathbf{K}_{\mathbf{H}\mathbf{H}}$ . Here the third step follows from the identity  $\det(\mathbf{I}_n + \mathbf{A}\mathbf{B}) = \det(\mathbf{I}_n + \mathbf{B}\mathbf{A})$ ; the fourth step follows from (5) which implies that  $\mathbf{A}^2 \mathbf{I}_n - \mathbb{X}^\dagger \mathbb{X}$  is positive semidefinite with probability one; the fifth step follows from the definition of SNR (4); and the last step follows because the determinant of a matrix is given by the product of its eigenvalues.

To evaluate the RHS of (17) in the limit as  $n$  tends to infinity, we apply Szegő's Theorem on the asymptotic behavior of the eigenvalues of Hermitian Toeplitz matrices [8] (see also [9, Thm. 2.7.13]). We obtain

$$\begin{aligned}
\lim_{n \rightarrow \infty} \frac{1}{n} I(H_1^n; Y_1^n | X_1^n) &\leq \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{k=1}^n \log(1 + \text{SNR} \lambda_k) \\
&= \int_{-1/2}^{1/2} \log(1 + \text{SNR} F'(\lambda)) d\lambda. \tag{18}
\end{aligned}$$

Combining (10), (12), (13), and (18) yields the final lower bound

$$\begin{aligned}
C(\text{SNR}) &\geq \Pr[|H_1| \geq \Upsilon] \log \text{SNR} - \Pr[|H_1| \geq \Upsilon] (1 - \log \Upsilon^2) \\
&\quad - \int_{-1/2}^{1/2} \log(1 + \text{SNR} F'(\lambda)) d\lambda, \tag{19}
\end{aligned}$$

SNR > 0,

which holds for any fixed  $\Upsilon > 0$ . Note that this lower bound applies to all mean- $d$ , unit-variance, stationary & ergodic fading processes  $\{H_k, k \in \mathbb{Z}\}$  with spectral distribution function  $F(\cdot)$ .

### 5.1.2 Asymptotic Analysis

In the following we prove (8) by computing the limiting ratio of the lower bound (19) to  $\log \text{SNR}$  as SNR tends to infinity.

We first show that

$$\lim_{\text{SNR} \rightarrow \infty} \int_{-1/2}^{1/2} \frac{\log(1 + \text{SNR} F'(\lambda))}{\log \text{SNR}} d\lambda = \mu(\{\lambda: F'(\lambda) > 0\}). \tag{20}$$

To this end, we divide the integral into three parts, depending on whether  $\lambda$  takes part in the set  $\mathcal{S}_1$ ,  $\mathcal{S}_2$ , or  $\mathcal{S}_3$ , where

$$\mathcal{S}_1 \triangleq \{\lambda \in [-1/2, 1/2]: F'(\lambda) = 0\} \tag{21}$$

$$\mathcal{S}_2 \triangleq \{\lambda \in [-1/2, 1/2]: F'(\lambda) \geq 1\} \tag{22}$$

$$\mathcal{S}_3 \triangleq \{\lambda \in [-1/2, 1/2]: 0 < F'(\lambda) < 1\}. \tag{23}$$

For  $\lambda \in \mathcal{S}_1$  the integrand is zero and hence

$$\lim_{\text{SNR} \rightarrow \infty} \int_{\mathcal{S}_1} \frac{\log(1 + \text{SNR} F'(\lambda))}{\log \text{SNR}} d\lambda = 0. \tag{24}$$

For  $\lambda \in \mathcal{S}_2$ , i.e., when  $F'(\lambda) \geq 1$ , we note that for sufficiently large SNR the function

$$\text{SNR} \mapsto \frac{\log(1 + \text{SNR} F'(\lambda))}{\log \text{SNR}}$$

is monotonically decreasing in SNR. Therefore, applying the Monotone Convergence Theorem [10, Thm. 1.26], we have

$$\begin{aligned} \lim_{\text{SNR} \rightarrow \infty} \int_{\mathcal{S}_2} \frac{\log(1 + \text{SNR} F'(\lambda))}{\log \text{SNR}} d\lambda &= \int_{\mathcal{S}_2} \lim_{\text{SNR} \rightarrow \infty} \frac{\log(1 + \text{SNR} F'(\lambda))}{\log \text{SNR}} d\lambda \\ &= \mu(\mathcal{S}_2) \\ &= \mu(\{\lambda: F'(\lambda) \geq 1\}). \end{aligned} \quad (25)$$

For  $\lambda \in \mathcal{S}_3$ , i.e., when  $0 < F'(\lambda) < 1$ , we have

$$0 < \frac{\log(1 + \text{SNR} F'(\lambda))}{\log \text{SNR}} < \frac{\log(1 + \text{SNR})}{\log \text{SNR}} \leq \log(1 + e), \quad \text{SNR} \geq e, \quad (26)$$

where the last step follows because, for sufficiently large SNR, the function

$$\text{SNR} \mapsto \frac{\log(1 + \text{SNR})}{\log \text{SNR}}$$

is monotonically decreasing in SNR. Since  $\log(1 + e)$  is integrable over  $\mathcal{S}_3$ , we can apply the Dominated Convergence Theorem [10, Thm. 1.34] to obtain

$$\begin{aligned} \lim_{\text{SNR} \rightarrow \infty} \int_{\mathcal{S}_3} \frac{\log(1 + \text{SNR} F'(\lambda))}{\log \text{SNR}} d\lambda &= \int_{\mathcal{S}_3} \lim_{\text{SNR} \rightarrow \infty} \frac{\log(1 + \text{SNR} F'(\lambda))}{\log \text{SNR}} d\lambda \\ &= \mu(\mathcal{S}_3) \\ &= \mu(\{\lambda: 0 < F'(\lambda) < 1\}). \end{aligned} \quad (27)$$

Adding (24), (25), and (27) yields (20).

To continue with the asymptotic analysis of (19) we note that by (20)

$$\begin{aligned} \Pi &\triangleq \overline{\lim_{\text{SNR} \rightarrow \infty}} \frac{C(\text{SNR})}{\log \text{SNR}} \\ &\geq \Pr[|H_1| \geq \Upsilon] - \mu(\{\lambda: F'(\lambda) > 0\}) \\ &= \mu(\{\lambda: F'(\lambda) = 0\}) - \Pr[|H_1| < \Upsilon] \end{aligned} \quad (28)$$

for any  $\Upsilon > 0$ . If the law of the fading process has no mass point at zero, then

$$\lim_{\Upsilon \downarrow 0} \Pr[|H_1| < \Upsilon] = 0, \quad (29)$$

and (8) therefore follows from (28) by letting  $\Upsilon$  tend to zero from above.

## 5.2 Proof of Note 1

We prove Note 1 by demonstrating that there exists a stationary & ergodic fading process of some spectral distribution function  $F(\cdot)$  for which

$$\Pi < \mu(\{\lambda: F'(\lambda) = 0\}).$$

By Theorem 1, the law of such a process must have a mass point at zero, i.e.,

$$\Pr[H_k = 0] > 0, \quad k \in \mathbb{Z}.$$

To this end, we first show that the capacity pre-log is upper bounded by

$$\Pi \leq \Pr[|H_1| > 0]. \quad (30)$$

Indeed, the capacity  $C(\text{SNR})$  does not decrease when the receiver additionally knows the realization of  $\{H_k, k \in \mathbb{Z}\}$ , and when the inputs have to satisfy an average-power constraint rather than a peak-power constraint, i.e.,

$$C(\text{SNR}) \leq \lim_{n \rightarrow \infty} \frac{1}{n} \sup I(X_1^n; Y_1^n | H_1^n), \quad (31)$$

where the maximization is over all input distributions on  $X_1, \dots, X_n$  satisfying the average-power constraint

$$\frac{1}{n} \sum_{k=1}^n \frac{\mathbb{E}[|X_k|^2]}{\sigma^2} \leq \text{SNR}. \quad (32)$$

(This follows because the availability of additional information cannot decrease the capacity, and because any distribution on the inputs satisfying the peak-power constraint (5) satisfies also (32).) It is well known that the expression on the RHS of (31) is equal to

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sup I(X_1^n; Y_1^n | H_1^n) = \mathbb{E}[\log(1 + |H_1|^2 \text{SNR})] \quad (33)$$

(e.g., [11, eq. (3.3.10)]), which can be further upper bounded by

$$\begin{aligned} \mathbb{E}[\log(1 + |H_1|^2 \text{SNR})] &= \Pr[|H_1| > 0] \mathbb{E}[\log(1 + |H_1|^2 \text{SNR}) \mid |H_1| > 0] \\ &\leq \Pr[|H_1| > 0] \log(1 + \mathbb{E}[|H_1|^2 \mid |H_1| > 0] \text{SNR}) \\ &= \Pr[|H_1| > 0] \log\left(1 + \frac{\text{SNR}}{\Pr[|H_1| > 0]}\right). \end{aligned} \quad (34)$$

Here the first step follows by writing the expectation as

$$\begin{aligned} \mathbb{E}[\log(1 + |H_1|^2 \text{SNR})] &= \Pr[|H_1| = 0] \mathbb{E}[\log(1 + |H_1|^2 \text{SNR}) \mid |H_1| = 0] \\ &\quad + \Pr[|H_1| > 0] \mathbb{E}[\log(1 + |H_1|^2 \text{SNR}) \mid |H_1| > 0], \end{aligned}$$

and by noting then that  $\mathbb{E}[\log(1 + |H_1|^2 \text{SNR}) \mid |H_1| = 0] = 0$ ; the second step follows from Jensen's inequality; and the last step follows because  $\mathbb{E}[|H_1|^2] = 1$ , which implies

$$\mathbb{E}[|H_1|^2 \mid |H_1| > 0] = \frac{1}{\Pr[|H_1| > 0]}.$$

Dividing the RHS of (34) by  $\log \text{SNR}$ , and computing the limit as  $\text{SNR}$  tends to infinity yields (30).

In view of (30), it suffices to demonstrate that there exists a fading process of some spectral distribution function  $F(\cdot)$  that satisfies

$$\Pr[|H_1| > 0] < \mu(\{\lambda : F'(\lambda) = 0\}). \quad (35)$$

A first attempt of defining such a process (which, alas, does not work) is

$$\dots, H_{-1}, H_0, H_1, H_2, \dots = \begin{cases} \dots, 0, 0, 0, 0, \dots & \text{with probability } \delta \\ \dots, B_{-1}, B_0, B_1, B_2, \dots & \text{with probability } 1 - \delta, \end{cases} \quad (36)$$

where  $\{B_k, k \in \mathbb{Z}\}$  is a zero-mean, circularly-symmetric, stationary & ergodic, complex Gaussian process of variance  $1/(1 - \delta)$  and of spectral distribution function  $G(\cdot)$ ; and where  $\delta$  and  $G(\cdot)$  are chosen so that

$$1 - \delta < \mu(\{\lambda : G'(\lambda) = 0\}). \quad (37)$$

This process satisfies (35) because  $\Pr[|H_1| > 0] = 1 - \delta$ , and because

$$\mathbb{E}[(H_{k+m} - d)(H_k - d)^*] = (1 - \delta) \mathbb{E}[B_{k+m} B_k^*], \quad (38)$$

which implies that  $F(\lambda) = (1 - \delta)G(\lambda)$  almost everywhere, so

$$\mu(\{\lambda : F'(\lambda) = 0\}) = \mu(\{\lambda : G'(\lambda) = 0\}). \quad (39)$$

Alas, the above fading process is stationary but not ergodic.

In the following, we exhibit a fading process that is stationary & ergodic and satisfies (35). Let

$$\dots, A_{-1}, A_0, A_1, A_2, \dots = \begin{cases} \dots, 0, 1, 0, 1, \dots & \text{with probability } \frac{1}{2} \\ \dots, 1, 0, 1, 0, \dots & \text{with probability } \frac{1}{2}, \end{cases} \quad (40)$$

and let  $\{B_k, k \in \mathbb{Z}\}$  be a zero-mean, variance-2, circularly-symmetric, stationary & ergodic, complex Gaussian process of spectral distribution function  $G(\cdot)$ . Furthermore let  $\{A_k, k \in \mathbb{Z}\}$  and  $\{B_k, k \in \mathbb{Z}\}$  be independent of each other. We shall consider fading processes of the form

$$H_k = A_k \cdot B_k, \quad k \in \mathbb{Z}. \quad (41)$$

Note that  $\{H_k, k \in \mathbb{Z}\}$  is of zero mean, and its law has a mass point at zero

$$\Pr[|H_k| > 0] = \Pr[A_k = 1] = \frac{1}{2}, \quad k \in \mathbb{Z}. \quad (42)$$

We first argue that  $\{H_k, k \in \mathbb{Z}\}$  is stationary & ergodic. Indeed,  $\{A_k, k \in \mathbb{Z}\}$  is stationary & ergodic. And since a Gaussian process is ergodic if, and only if, it is weakly-mixing (see, e.g., [12, Sec. II]), we have that  $\{B_k, k \in \mathbb{Z}\}$  is stationary & weakly-mixing. (See [13, Sec. 2.6] for a definition of weakly-mixing stochastic processes.) It thus follows from [14, Prop. 1.6] that the process  $\{(A_k, B_k), k \in \mathbb{Z}\}$  is jointly stationary & ergodic, which implies that  $\{H_k, k \in \mathbb{Z}\} = \{A_k \cdot B_k, k \in \mathbb{Z}\}$  is stationary & ergodic.

We next demonstrate that  $G(\cdot)$  can be chosen so that  $\{H_k, k \in \mathbb{Z}\}$  satisfies (35). We choose

$$G'(\lambda) = \begin{cases} \frac{1}{W}, & \text{if } |\lambda| \leq W \\ 0, & \text{otherwise} \end{cases} \quad (43)$$

for some  $W \in (0, 1/8)$ , which corresponds to the autocovariance function

$$\mathbb{E}[B_{k+m} B_k^*] = 2 \operatorname{sinc}(2Wm), \quad m \in \mathbb{Z}.$$

Here  $\operatorname{sinc}(\cdot)$  denotes the sinc-function, i.e.,  $\operatorname{sinc}(x) = \sin(\pi x)/(\pi x)$  for  $|x| > 0$  and  $\operatorname{sinc}(0) = 1$ . Using that

$$\mathbb{E}[A_{k+m} A_k^*] = \frac{1}{2} \mathbb{I}\{m \text{ is even}\}, \quad m \in \mathbb{Z}$$

(where  $\mathbb{I}\{\text{statement}\}$  is 1 if the statement is true, and 0 otherwise), we have for the autocovariance function of  $\{H_k, k \in \mathbb{Z}\}$

$$\begin{aligned} \mathbb{E}[H_{k+m} H_k^*] &= \mathbb{E}[A_{k+m} B_{k+m} A_k^* B_k^*] \\ &= \mathbb{E}[A_{k+m} A_k^*] \mathbb{E}[B_{k+m} B_k^*] \\ &= \mathbb{I}\{m \text{ is even}\} \cdot \operatorname{sinc}(2Wm), \quad m \in \mathbb{Z}, \end{aligned} \quad (44)$$

and the corresponding spectrum is given by

$$F'(\lambda) = \begin{cases} \frac{1}{4W}, & \text{if } |\lambda| \leq W \text{ or } \frac{1}{2} - W \leq |\lambda| \leq \frac{1}{2} \\ 0, & \text{otherwise.} \end{cases} \quad (45)$$

Evaluating the Lebesgue measure of the set of harmonics where  $F'(\lambda) = 0$ , we have

$$\mu(\{\lambda: F'(\lambda) = 0\}) = 1 - 4W, \quad (46)$$

and it follows from (42) that

$$\Pr[|H_k| > 0] = \frac{1}{2} < \mu(\{\lambda: F'(\lambda) = 0\}), \quad \text{for } W < \frac{1}{8}.$$

Thus there exist stationary & ergodic fading processes whose law has a mass point at zero and that give rise to a capacity pre-log that is strictly smaller than the pre-log of a Gaussian fading channel of equal spectral distribution function.

### 5.3 Proof of Note 2

To prove Note 2, we first notice that, since the phase noise is memoryless, the derivative of the spectral distribution function is

$$F'(\lambda) = 1, \quad -\frac{1}{2} \leq \lambda \leq \frac{1}{2}.$$

Hence the capacity pre-log of the Gaussian fading channel of spectral distribution function  $F(\cdot)$  equals

$$\Pi_G = \mu(\{\lambda: F'(\lambda) = 0\}) = 0. \quad (47)$$

It thus remains to show that the pre-log of the phase-noise channel with memoryless phase noise is equal to

$$\Pi = \frac{1}{2}. \quad (48)$$

In [15] it was shown that at high SNR the capacity of the phase-noise channel under an average-power constraint on the inputs is given by

$$C_{\text{Avg}}(\text{SNR}) = \frac{1}{2} \log\left(1 + \frac{\text{SNR}}{2}\right) + o(1), \quad (49)$$

where  $o(1)$  tends to zero as SNR tends to zero. (The subscript “Avg” indicates that the inputs satisfy an average-power constraint and not a peak-power constraint.) Since any distribution on the inputs satisfying the peak-power constraint (5) satisfies also the average-power constraint, it follows that  $C(\text{SNR}) \leq C_{\text{Avg}}(\text{SNR})$  and hence

$$\Pi \leq \frac{1}{2}. \quad (50)$$

To prove (48) it thus suffices to show that  $\Pi \geq \frac{1}{2}$ . To this end, we first note that, since the phase noise is memoryless, we have

$$C(\text{SNR}) = \sup I(X_1; Y_1), \quad (51)$$

where the maximization is over all distributions on  $X_1$  satisfying with probability one

$$|X_1| \leq A.$$

We derive a lower bound on  $C(\text{SNR})$  by evaluating the RHS of (51) for  $X_1$  being a zero-mean, circularly-symmetric, complex random variable with  $|X_1|^2$  uniformly distributed over the interval  $[0, A^2]$ . We have

$$\begin{aligned} I(X_1; Y_1) &\geq I(X_1; |Y_1|^2) \\ &= h(|Y_1|^2) - h(|Y_1|^2 | X_1) \\ &\geq h(|X_1|^2) - h(|Y_1|^2 | X_1), \end{aligned} \quad (52)$$

where the first step follows from the data processing inequality [4, Thm. 2.8.1]; and the last step follows by the circular symmetry of  $X_1$  [15, p. 3, after eq. (20)].

Computing the differential entropy of a uniformly distributed random variable, the first term on the RHS of (52) becomes

$$h(|X_1|^2) = \log A^2. \quad (53)$$

As to the second term, we note that, for a given  $X_1 = x_1$ , the random variable  $2/\sigma^2 |Y_1|^2$  has a noncentral chi-square distribution with noncentrality parameter  $2/\sigma^2 |x_1|^2$  and two degrees of freedom. Its differential entropy can be upper bounded by [15, eq. (8)]

$$\begin{aligned} h(|Y_1|^2 | X_1) &\leq \frac{1}{2} \mathbb{E} \left[ \log \left( 4\pi e \left( 2 + 2 \frac{2}{\sigma^2} |X_1|^2 \right) \right) \right] - \log \frac{2}{\sigma^2} \\ &\leq \frac{1}{2} \log \left( 4\pi e \left( 2 + 2 \frac{2}{\sigma^2} A^2 \right) \right) - \log \frac{2}{\sigma^2}, \end{aligned} \quad (54)$$

where the last step follows because  $|X_1| \leq A$  with probability one. Combining (53) and (54) with (52) yields thus

$$I(X_1; Y_1) \geq \frac{1}{2} \log \text{SNR} + o(\log \text{SNR}), \quad (55)$$

where

$$\lim_{\text{SNR} \rightarrow \infty} \frac{o(\log \text{SNR})}{\log \text{SNR}} = 0.$$

We finally obtain the lower bound

$$\Pi \geq \frac{1}{2}$$

upon dividing the RHS of (55) by  $\log \text{SNR}$  and letting then SNR tend to infinity.

## 6 Extension to MISO Fading Channels

Theorem 1 can be extended to multiple-input single-output (MISO) fading channels with memory, when the fading processes corresponding to the different transmit antennas are independent. For such channels, the channel output  $Y_k \in \mathbb{C}$  at time  $k \in \mathbb{Z}$  corresponding to the channel input  $\mathbf{x}_k \in \mathbb{C}^{n_T}$  (where  $n_T$  stands for the number of antennas at the transmitter) is given by

$$Y_k = \mathbf{H}_k^T \mathbf{x}_k + Z_k, \quad k \in \mathbb{Z}, \quad (56)$$

where  $\mathbf{H}_k = \left( H_k^{(1)}, \dots, H_k^{(n_T)} \right)^T$ , and where the processes

$$\{H_k^{(1)}, k \in \mathbb{Z}\}, \{H_k^{(2)}, k \in \mathbb{Z}\}, \dots, \{H_k^{(n_T)}, k \in \mathbb{Z}\}$$

are jointly stationary & ergodic and independent. We assume that for each  $t = 1, \dots, n_T$  the process  $\{H_k^{(t)}, k \in \mathbb{Z}\}$  is of mean  $d_t$ , of unit variance, and of spectral distribution function  $F_t(\cdot)$ . We further assume that

$$\Pr[H_k^{(1)} = 0] = \Pr[H_k^{(2)} = 0] = \dots = \Pr[H_k^{(n_T)} = 0] = 0, \quad k \in \mathbb{Z}. \quad (57)$$

The additive noise  $\{Z_k, k \in \mathbb{Z}\}$  is defined as in Section 2.

The capacity of this channel is given by (3), but with  $X_1^n$  replaced by  $\mathbf{X}_1^n$ , and with the peak-power constraint (5) altered accordingly:

$$\|\mathbf{X}_k\| \leq A \quad \text{with probability one,} \quad k \in \mathbb{Z}, \quad (58)$$

where  $\|\mathbf{a}\|$  denotes the Euclidean norm of the vector  $\mathbf{a}$ , i.e.,

$$\|\mathbf{a}\| = \sqrt{\sum_{\ell=1}^L |a_\ell|^2}, \quad \mathbf{a} = (a_1, \dots, a_L)^T. \quad (59)$$

Let  $\Xi$  denote the pre-log of MISO fading channels. Following (6), we define  $\Xi$  as

$$\Xi \triangleq \overline{\lim}_{\text{SNR} \rightarrow \infty} \frac{C(\text{SNR})}{\log \text{SNR}}. \quad (60)$$

For Gaussian fading, i.e., when  $\{H^{(t)} - d_t, k \in \mathbb{Z}\}$ ,  $1 \leq t \leq n_T$  are circularly-symmetric, complex Gaussian processes, the pre-log was shown to be given by [16, Cor. 13]

$$\Xi_G = \max_{1 \leq t \leq n_T} \mu(\{\lambda: F_t'(\lambda) = 0\}). \quad (61)$$

(A proof of this result can be found in [17, Sec. 7.2.2].)

Proving that the capacity pre-log  $\Xi$  of MISO fading channels is lower bounded by the pre-log of the MISO Gaussian fading channel of equal spectral distribution functions—namely

$F_1(\cdot), \dots, F_{n_T}(\cdot)$ —is straightforward. Let  $\Pi_t$ ,  $1 \leq t \leq n_T$  denote the capacity pre-log of a single-antenna fading channel with fading process  $\{H_k^{(t)}, k \in \mathbb{Z}\}$ , and let

$$t_\star = \arg \max_{1 \leq t \leq n_T} \Pi_t.$$

By signaling only from antenna  $t_\star$  while keeping the others silent, we can achieve the pre-log  $\Pi_{t_\star}$ , so

$$\Xi \geq \max_{1 \leq t \leq n_T} \Pi_t. \quad (62)$$

Theorem 1 yields then

$$\Pi_t \geq \mu(\{\lambda: F'_t(\lambda) = 0\}), \quad 1 \leq t \leq n_T, \quad (63)$$

which together with (62) proves the claim

$$\Xi \geq \max_{1 \leq t \leq n_T} \mu(\{\lambda: F'_t(\lambda) = 0\}). \quad (64)$$

## 7 Summary and Discussion

We showed that, among all stationary & ergodic fading processes of a given spectral distribution function and whose law has no mass point at zero, the Gaussian process gives rise to the smallest capacity pre-log. We further showed that if the fading law is allowed to have a mass point at zero, then the above statement is not necessarily true anymore. Roughly speaking, we can say that for a large class of fading processes the Gaussian process is the worst. This demonstrates the robustness of the Gaussian assumption in the analysis of fading channels at high SNR.

To give an intuition why Gaussian processes give rise to the smallest pre-log, we recall that for Gaussian fading [1, eqs. (33) & (47)]

$$C(\text{SNR}) = \log \frac{1}{\epsilon_{\text{pred}}^2(1/\text{SNR})} + o(\log \text{SNR}),$$

where  $\epsilon_{\text{pred}}^2(\delta)$  denotes the mean-square error in predicting the present fading  $H_0$  from a variance- $\delta$  noisy observation of its past  $H_{-1} + W_{-1}, H_{-2} + W_{-2}, \dots$  (with  $\{W_k, k \in \mathbb{Z}\}$  being a sequence of IID, zero-mean, variance- $\delta$ , circularly-symmetric, complex Gaussian random variables). Thus for Gaussian fading the capacity pre-log is determined by  $\epsilon_{\text{pred}}^2(1/\text{SNR})$ , and it is plausible that also the pre-log of non-Gaussian fading channels is connected with the ability of predicting the present fading from a noisy observation of its past. Since, among all stationary & ergodic processes of a given spectral distribution function, the Gaussian process is hardest to predict, it is therefore plausible that the Gaussian process gives rise to the smallest pre-log.

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